UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE

DTIC FILE COPY

2

AD-A218 722

REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1b. RESTRICTIVE MARKINGS

3. DISTRIBUTION/AVAILABILITY OF REPORT
Approved for public release; distribution is unlimited.

2b. DECLASSIFICATION/DOWNGRADING SCHEDULE

4. PERFORMING ORGANIZATION REPORT NUMBER(S)
USAFSAM-JA-89-48

5. MONITORING ORGANIZATION REPORT NUMBER(S)

6a. NAME OF PERFORMING ORGANIZATION
USAF School of Aerospace Medicine

6b. OFFICE SYMBOL (If applicable)
USAFSAM/NGFO

7a. NAME OF MONITORING ORGANIZATION

6c. ADDRESS (City, State, and ZIP Code)
Human Systems Division (AFSC)
Brooks Air Force Base, TX 78235-5301

7b. ADDRESS (City, State, and ZIP Code)

8a. NAME OF FUNDING/SPONSORING ORGANIZATION
USAF School of Aerospace Medicine

8b. OFFICE SYMBOL (If applicable)
USAFSAM/NGFO

9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER

8c. ADDRESS (City, State, and ZIP Code)
Human Systems Division (AFSC)
Brooks Air Force Base, TX 78235-5301

10. SOURCE OF FUNDING NUMBERS

PROGRAM ELEMENT NO.	PROJECT NO.	TASK NO	WORK UNIT ACCESSION NO.
62202F	7755	27	15

11. TITLE (Include Security Classification)
A New Approach to the Analysis of Nystagmus: An Application for Order-Statistic Filter

12. PERSONAL AUTHOR(S)
Engelken, Edward J., and Stevens, Kennith W.

13a. TYPE OF REPORT
Interim

13b. TIME COVERED
FROM 89/01 TO 89/08

14. DATE OF REPORT (Year, Month, Day)

15. PAGE COUNT
05

16. SUPPLEMENTARY NOTATION

17. COSATI CODES

FIELD	GROUP	SUB-GROUP
06	05	
14	02	

18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
Nystagmus; Order-Statistic Filters; Nonlinear Filters; Adaptive Filter

19. ABSTRACT (Continue on reverse if necessary and identify by block number)
A computer program has been designed for the analysis of nystagmus. This program employs a class of nonlinear digital filters called order-statistic (OS) filters. Two OS filters and one linear filter are used. First, the eye-movement signal is smoothed using a predictive FIR-median hybrid filter. Then the smoothed signal is processed by a linear band-limited differentiating filter to calculate eye velocity. And, finally, the slow-phase velocity (SPV) envelope is extracted from the eye-velocity signal using an adaptive asymmetrically trimmed-mean filter. This approach yields an evenly sampled SPV estimate without resorting to the various interpolation or extrapolation schemes generally used. The adaptive filter estimates SPV based on the local statistical properties of the eye-velocity signal. The adaptive strategy works under the assumption that, on the average, the eyes spend more time in slow-phase than in fast-phase. No assumptions are made about the directions of the nystagmus or the nature of the stimulus used to elicit the nystagmus. This method eliminates all the usual threshold tests and decision logic common to other nystagmus analysis

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT
☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT ☐ DTIC USERS

21. ABSTRACT SECURITY CLASSIFICATION
Unclassified

22a. NAME OF RESPONSIBLE INDIVIDUAL
Edward J. Engelken

22b. TELEPHONE (Include Area Code)
(512)536-3201

22c. OFFICE SYMBOL
USAFSAM/NGFO

DD Form 1473, JUN 86 Previous editions are obsolete.

SECURITY CLASSIFICATION OF THIS PAGE

UNCLASSIFIED

Item 19. ABSTRACT (CONT)

programs. The robust performance of OS filters and the use of adaptive filter structures totally eliminates the need to custom "tune" the program parameters for atypical data sets.

X

A-1

A New Approach to the Analysis of Nystagmus: An Application for Order-Statistic Filters

Edward J. Engelken, M.S., Ph.D.
Kennith W. Stevens, B.S.

USAF School of Aerospace Medicine
Clinical Sciences Division
Brooks AFB, TX 78235-5301

RUNNING HEAD: Analysis of Nystagmus

ADDRESS CORRESPONDENCE TO:
Dr. Edward J. Engelken
USAFSAM/NGFO
Brooks AFB, TX 78235-5301
(512) 536-3201

October 23, 1989

Abstract

A computer program has been designed for the analysis of nystagmus. This program employs a class of nonlinear digital filters called order-statistic (OS) filters. Two OS filters and one linear filter are used. First, the eye-movement signal is smoothed using a predictive FIR-median hybrid filter. Then the smoothed signal is processed by a linear band-limited differentiating filter to calculate eye velocity. And, finally, the slow-phase velocity (SPV) envelope is extracted from the eye-velocity signal using an adaptive asymmetrically trimmed-mean filter. This approach yields an evenly sampled SPV estimate without resorting to the various interpolation or extrapolation schemes generally used. The adaptive filter estimates SPV based on the local statistical properties of the eye-velocity signal. The adaptive strategy works under the assumption that, on the average, the eyes spend more time in slow-phase than in fast-phase. No assumptions are made about the direction of the nystagmus or the nature of the stimulus used to elicit the nystagmus. This method eliminates all the [illegible] threshold tests and decision logic common to other nystagmus analysis programs. The robust performance of OS filters and the use of adaptive filter structures totally eliminates the need to custom "tune" the program parameters for atypical data sets.

[1]KEY WORDS: Digital Filters, Nonlinear Filters, Adaptive Filters, Vestibular System, Optokinetic System

INTRODUCTION

When one observes a continuously moving visual scene or experiences continuous rotation, a form of reflexive eye movement called nystagmus is induced. This reflexive eye movement maintains the image of the visual world stationary on the retinae despite the motion. Nystagmus consists of a sequence of motion-compensating movements called slow-phase interspersed with quick refixation movements called fast-phase. Generally, the fast-phase is in the opposite direction to the slow-phase, but a few like-directed fast-phase movements are often observed. Nystagmus is termed optokinetic if induced by visual stimulation or vestibular if evoked bv head rotation or other stimulation of the vestibular system. Both optokinetic and vestibular nystagmus are routinely studied in the clinical setting. Optokinetic responses are useful in the detection of central nervous system disorders [8]; vestibular nystagmus induced by whole body rotation or caloric stimulation is employed in the evaluation of the vestibulo-ocular reflex [17, 24, 25]. Optokinetic and vestibular responses are important in flight; both play an important role in spatial disorientation and the generation of various illusions of motion.

The usual parameter of interest in the evaluation of nystagmus is slow-phase velocity (SPV) and sometimes, cumulative slow-phase eye position. In the analysis of nystagmus, the refixation component (fast-phase) is generally treated as an undesired interruption of the compensatory process. It has been standard practice to attempt to eliminate the fast-phase from the eye-position or eye-velocity record, usually by means of a fast-phase identification algorithm followed by an extrapolation [1, 12, 23] or interpolation [5, 10, 26] procedure. Identification of the fast-phase is based on assumed differences in the velocity, acceleration, and duration characterstics of the slow- and fast-phase. Unfortunately, these differences do not always provide adequate discrimination; a slower-than-average fast-phase can be mistaken for a faster-than-average slow-phase. The common practice of using linear low-pass filters to remove EMG and other high-frequency noise exacerbates the problem by smearing the fast-phase causing it to more resemble a slow-

[1]From the USAF School of Aerospace Medicine's Clinical Sciences Division, Brooks AFB, TX, where Dr. Engelken is Chief of the Vestibular Laboratory.
Send reprint requests to Dr. Engelken at USAFSAM/NGFO, Brooks AFB, TX 78235-5301.

phase. To overcome these shortcomings, some authors have included extra information in the fast-phase identification algorithm, information such as the expected direction of the fast-phase, or the nature of the stimulus that elicited the nystagmus [5, 6]. Taking a different approach, others have used iterative procedures to fit the eye-movement signal to the expected response waveform [3, 4]. Increasing the number of assumptions about the stimulus signal or the expected response restricts the flexibility of the analysis program and makes processing atypical recordings difficult. Others have supplemented their automated procedures with an editing function that allows a human operator to "touch-up" problem areas in the data using an interactive graphics system [2, 10]. Such manual editing of data is time consuming and introduces operator variability into the data analysis process. Our dissatisfaction with the currently available nystagmus analysis methods has prompted us to seek a new approach.

ANALYSIS APPROACH

We have developed new methods for the analysis of nystagmus using a class of nonlinear digital filters called order-statistic (OS) filters. The entire analysis program consists of a series of three digital filters (two OS filters and one linear filter) as shown in Fig. 1. An OS filter termed a Predictive FIR-Median Hybrid (PFMH) filter [15] is used to smooth the nystagmus. This filter design is based on the principle that the nystagmus signal can be reasonably modeled as a piecewise continuous sequence of second-order polynomial segments. Application of the filter attenuates signal components that are not consistent with this signal model. Since sharp changes between well behaved regions (such as the transition from slow- to fast-phase) are consistent with the signal model, the transitions are preserved. Of course, the ramp-like slow- and fast-phases themselves are preserved as well. Oscillations and impulses are not consistent with the signal model and are suppressed. The PFMH filter smooths the slow- and fast-phases without altering their slopes or blurring the boundary between them.

Eye velocity is calculated from the smoothed nystagmus signal using a standard band-limited differentiating filter [11]. Then SPV is extracted from the eye-velocity record using an adaptive asymmetrically trimmed-mean

(AATM) filter. The AATM filter operates on a .5 to 1-s wide sliding window of data centered at the current point of interest. The statistical properties of the velocity data in the window are used to select a subset of the data to be averaged. This selection process includes only SPV data samples in the average. The averaged SPV is taken to be the filter output at the point of interest. As the sliding window is moved across the velocity data, the AATM filter produces an evenly sampled estimate of SPV.

ORDER STATISTIC FILTERS

A considerable body of theory on OS filters has been developed [9, 13, 18, 19, 20]. The reader is referred to these articles for details; only a few essential properties of OS filters will be discussed here.

OS filters are a class of nonlinear digital filters that operate on a sliding window of input data samples. Usually the window is of odd length; i.e., $L = 2N + 1$. The samples in the window are rank-ordered and the ordered samples (order statistics) are linearily weighted. This linear combination of order statistics constitutes the filter output. For example, the standard median filter is an OS filter in which the center sample of the ordered array is given a weight of 1 and all other samples a weight of 0. Other OS filters are implemented by choosing different weighting coefficients. The OS filter concept can be extended to include a class of filters introduced by Heinonen and Neuvo [14, 15] termed FIR-Median Hybrid (FMH) filters. In the FMH filter, data samples are first processed by a set of finite-impulse-response (FIR) subfilters and then the median of the FIR subfilter outputs is taken as the FMH filter output. The key element in all OS filters is the rank-ordering operation; a data dependent, nonlinear process. OS filters are nonlinear in the sense that the principle of superposition does not apply. If we define the operation of OS filtering as $OS\{\cdot\}$, then in general $OS\{u(n) + v(n)\} \neq OS\{u(n)\} + OS\{v(n)\}$ where $u(n)$ and $v(n)$ are different time varying signals. The ordering operation is unaffected by multiplicative or additive constants, so that $OS\{A \cdot u(n) + B\} = A \cdot OS\{u(n)\} + B$ where A and B are constants. Therefore OS filtering is a scale and offset invariant operation.

An important property of the median filter and certain other OS filters is the existence of a class of signals, called root signals, that are invariant to further filtering, and that repeated filtering will reduce any signal to a root signal in a finite number of filtering operations [13, 19, 20].

SMOOTHING THE NYSTAGMUS

Intuitively, one would expect that if an underlying signal was a root signal for a given OS filter, that filter would be effective in extracting the signal from noise without distortion. That is, repeated OS filtering would reduce the noise contaminated signal to a root signal, and thereby recover the signal while rejecting the noise. Of course, it is possible that the root signal obtained will not be the desired signal if the noise is too great; the process may converge to a different root signal. The utility of this data smoothing method depends on the robustness of OS filters in recovering noise contaminated root signals. Our approach to smoothing the nystagmus signal was to design an OS filter with root signals that resemble an ideal nystagmus waveform.

Heinonen and Neuvo [15] introduced a new class of OS filters that can be designed with root signals that are piecewise continuous low-order polynomials. These root signals may include triangular- and sawtooth-like waves. Unlike the standard median filter, these new filters preserve the sharp "corners" on the waveforms. The authors termed these filters *predictive* FMH (PFMH) filters. The PFMH filter operates on a window, $W(n)$, of data samples, $x(j)$, of length $L = 2N + 1$, such that

$$W(n) = \{x(n-N), x(n-N+1), \ldots, x(n), \ldots, x(n+N)\}$$

The data samples *before* and *after* the center point, $x(n)$, are used to estimate the value *at* the center using predictive FIR filter substructures of the following form:

Forward predictor,

$$\hat{x}_F^r(n) = \sum_{i=1}^{N} h_r(i) \cdot x(n-i), \; i = 1, \ldots, N$$

Backward predictor,

$$\hat{x}_B^r(n) = \sum_{i=1}^{N} h_r(i) \cdot x(n+i), \; i = 1, \ldots, N$$

where $\hat{x}_F^r(n)$ and $\hat{x}_B^r(n)$ are the forward and backward predicted values and $h_r(i)$ is the coefficient array for the FIR predictor of order r.

The output of the PFMH filter is the median of the predicted values, and the data value $x(n)$. Thus, if the median operation is defined as $MED\{\cdot\}$, then the filter output $y(n)$ is given by

$$y(n) = MED\{\hat{x}_F^r(n), \hat{x}_F^{r-1}(n), \ldots, x(n), \ldots, \hat{x}_B^{r-1}(n), \hat{x}_B^r(n)\}$$

The zero-, first-, and second-order FIR predictor coefficients as given by Heinonen and Neuvo [15] are

$$h_0(i) = 1/N, \ i = 1, \ldots, N$$

$$h_1(i) = \frac{4N - 6i + 2}{N(N-1)}, \ i = 1, \ldots, N$$

$$h_2(i) = \frac{9N^2 + (9 - 36i)N + 30i^2 - 18i + 6}{N(N^2 - 3N + 2)}, \ i = 1, \ldots, N$$

These predictive substructures are optimal predictors for an rth-order polynomial contaminated by additive Gaussian white noise. Practical filter designs can use predictors up to about third-order. For the processing of nystagmus, we have been using four predictive substructures; three first-order predictors of different lengths, and one second-order predictor. The motivation for using a collection of predictors of different order and/or length is to have at least one that works well for each part of the signal. The median operation selects one of the candidates as the filter output and permits rapid switching between the candidates for different areas of the signal waveform.

Smoothing Filter Results

We recorded nystagmus signals using standard electrooculographic (EOG) methods. The signals were passed through a 30-Hz, low-pass, 4-pole Butterworth filter and then digitized at a sampling frequency of 128 Hz. A PFMH smoothing filter was designed using three first-order predictors of sizes, $N = 6$, $N = 15$ and $N = 24$, and a second-order predictor of size,

$N = 24$. Figure 2 shows the results of filtering a noisy nystagmus signal. Repeated application of the PFMH filter will drive the nystagmus signal towards a root signal. When a root signal is obtained, the original nystagmus signal will be reduced to a pure sequence of second-order polynomial segments. These will be the best-fitting polynomial segments in the least-squares sense. As can be seen in Fig. 2, it is not necessary to reduce the nystagmus to a root signal to obtain effective filtering. In most cases, one or two passes of the filter provides significant noise reduction.

CALCULATING EYE VELOCITY

We use a band-limited differentiating filter to calculate eye velocity from the smoothed eye-position (nystagmus) signal. This filter type has been described previously [11]. The design used in this application is a linear FIR band-limited differentiating filter with a cutoff frequency of 30 Hz. The filter length is 61 points. The smoothed nystagmus signal is processed by this filter to produce the eye-velocity signal.

ESTIMATING THE SPV

SPV is extracted from the eye-velocity signal based on the assumption that, on the average, the eyes spend more time in slow-phase than in fast-phase. Under this assumption, if we construct a .5 to 1-s moving window of eye-velocity samples, the dominant mode of the frequency histogram of the samples will indicate the slow-phase velocity (Fig 3). Our method for estimating SPV is to use an AATM filter to average velocity samples from the neighborhood of the dominant mode.

The AATM filter concept was first suggested by Hogg [16] to provide an efficient "estimator" for use with asymmetric distributions. Hogg discussed the error structure of the filter, but did not offer specific applications for it. Restrepo and Bovik[22] presented an application for an adaptive *symmetric* trimmed-mean filter and briefly alluded to the possibility of an *asymmetric* version; but no designs were given. The following paragraphs will describe our development of an AATM filter for nystagmus analysis by modifying the trimmed-mean filter.

The Trimmed-Mean Filter

The trimmed-mean filter (also called the alpha trimmed-mean filter) has been studied extensively [7, 9, 18, 21]. We will only present a few essential details.

The trimmed-mean filter operates on a moving window of data samples. The samples are rank-ordered from low to high, and a fraction of the samples are "trimmed" from each end of the ordered array. The remaining data samples are then averaged and constitute the filter output. The trimmed-mean filter is defined as follows:

Given a rank-ordered set (window) of data samples, W, of length $L = 2N + 1$, such that $W = \{x_1, x_2, \ldots, x_j, \ldots, x_L\}$ where $x_1 \leq x_2 \leq \cdots \leq x_L$ the trimmed-mean, TM_α, is given by

$$TM_\alpha = \frac{1}{L - 2[L\alpha]} \sum_{j=[L\alpha]+1}^{L-[L\alpha]} x_j$$

where α is the trimming fraction, $[L\alpha]$ is the integer part of $L\alpha$ (the number of samples trimmed from each end), and $0 \leq \alpha \leq 0.5$. The asymmetric TM filter (ATM) is derived from the TM filter by trimming an unequal number of data samples from each end of the ordered array before averaging. The ATM filter is defined as

$$ATM_{\alpha,K} = \frac{1}{L - 2[L\alpha]} \sum_{j=[L\alpha]+1+K}^{L-[L\alpha]+K} x_j$$

where K is the shift index and $-[L\alpha] \leq K \leq [L\alpha]$.

The AATM Filter

The AATM filter is derived from the ATM filter by making K a function of the data samples in the window.

The operation of the AATM filter in estimating SPV can be appreciated by examining the 1-s windows of nystagmus velocity samples given in Fig. 3. Notice that the frequency histograms of the velocity samples are skewed toward the fast-phase, and the SPV data samples are located around the dominant mode of the histogram. This condition will exist as long as the eyes spend more time in slow-phase than in fast-phase. If we could easily construct a true continuous frequency distribution function of the velocity samples, the dominant mode of this distribution would be a good estimator of SPV. A computationally efficient method to estimate the true dominant mode (hence SPV) is to use an AATM filter to average samples taken from around the dominant mode of the frequency histogram. No assumptions about the direction, velocity, or duration of the fast-phase are required. We only need to locate the dominante mode of the histogram to perform the averaging which can be done without actually constructing frequency histograms for each data window. The dominant mode can be located by proper evaluation of the the rank-ordered velocity samples. For example, if the histogram is symmetric, the median and the mode are colocated and we can average samples in the neighborhood of the median using the ATM filter with $K = 0$. If the histogram is skewed, then the dominant mode will shift above or below the median value. Our strategy in this case is to estimate the skewness of the histogram. Then, using this skewness estimate, we can adjust the shift index K of the ATM filter to position the "averaging window" around the dominant mode. To this end, we have devised the following skewness estimator

$$S_\beta = \frac{MAX_\beta + MIN_\beta - 2 \cdot MED}{MAX_\beta - MIN_\beta}$$

where

$$MAX_\beta = x_{L-[L\beta]}, \text{ the trimmed maximum}$$

$$MIN_\beta = x_{[L\beta]}, \text{ the trimmed minimum}$$

$$MED = x_{N+1}, \text{ the median.}$$

Skewness, S_β, is a simple combination of order statistics and is readily calculated from the rank-ordered data samples. Importantly, S_β is scale and offset invariant. The parameter β is chosen to balance noise immunity against sensitivity; practical values range from about 0.05 to 0.2. S_β has the property that $-1 \leq S_\beta \leq +1$. The ATM filter is made adaptive (i.e., an AATM filter) by setting the shift index in the ATM filter to $K = [MS_\beta]$, where M is the maximum shift index permitted. A block diagram of the AATM filter is given in Fig. 4.

The operation of the entire analysis program, including the AATM filter, is illustrated in Fig. 5. For the data presented in Fig. 5, we used an AATM filter with $L = 129$, $M = 24$, $\alpha = 0.44$, and $\beta = 0.12$. For this choice of parameters, the AATM filter operates using a sliding 1-s window of velocity samples. Skewness is calculated and subsets of 17 velocity samples are selected for each window position. The estimated SPV is the average of these 17 samples.

DISCUSSION

We have introduced a new approach to the analysis of nystagmus. The novel aspect of this approach is the use of OS filters to smooth the nystagmus signal and to estimate SPV. Unlike earlier methods, we estimate SPV without making detailed assumptions about the signal structure. No threshold testing is done, no pattern recognition methods are employed, and no interpolation or extrapolation procedures are used. SPV is estimated using only the local statistical properties of the nystagmus velocity signal. Minimizing the number of assumptions about the signal structure and using an adaptive estimator results in a robust analysis program that can handle a wide variety of nystagmus signals without adjusting program parameters. These methods are particulary useful when analyzing positional nystagmus and nystagmus induced by caloric stimulation or Hallpike maneuvers where the direction and/or time-course of the SPV can not be anticipated.

Despite the use of nonlinear OS filters, our analysis program has an important linear system property that previous methods lack. The entire processing algorithm is *scale invariant* which means that the program operation is totally independent of the calibration factors for the eye-movement signal. Thus, data recorded from infants or small children can be processed despite the lack of adequate calibration. Parameters such as the symmetry of the optokinetic and vestibulo-ocular reflexes, post-rotatory nystagmus time constants, etc., can be accurately measured without having calibration factors. The ability to precisely estimate unscaled SPV is especially important when analyzing nystagmus recorded in simulators, in flight, or in space, where environmental factors sometimes preclude accurate calibration of the eye-movement signal. Previous analysis methods [1, 2, 5, 6, 10, 23] depend upon a calibrated eye-movement signal in order to function, and cannot operate properly using unscaled data. Our approach overcomes this limitation.

Calibration factors are used only to scale the final SPV output.

Although these methods were developed to analyze nystagmus recorded using EOG methods, the program is equally suited to processing data recorded using search coils or infrared reflection devices. The design goal of the analysis program was to estimate SPV, but the procedures could be modified to provide an estimate of fast-phase velocity as well. Cumulative slow-phase eye position may be readily calculated by numerical integration of the SPV. The methods presented here are quite general and are applicable to the analysis of a variety of signals besides nystagmus.

The parameter values chosen for the PFMH and AATM filters were selected after exploring a large number of nystagmus records. We do not consider these choices to be optimum in any sense; they should be considered only as good operating values. We have been using the parameter values described herein for all nystagmus, except those generated by high-frequency rotations. For rotation at frequencies above 0.15 Hz, we reduce the length of the AATM filter to 0.5 s ($L = 65$). Since the AATM filter has an excellent step-function response, it is not necessary to reduce the filter length for step-velocity (impulse acceleration) stimuli. The program operation is not heavily dependent on the exact parameter values selected due to the robust performance of the OS filters.

We do not consider our methods to be the "final word", but rather, to be just the first step in the application of OS filters in nystagmus analysis. The rapid developments occuring in the field of OS filter theory will certainly provide improved methods in the future.

Acknowledgments

The authors gratefully acknowledge the technical support provided by Sgt. Gary Muniz, Sgt. Jerry Limburg, and Amn. Moises Ramirez.

The voluntary informed consent of the subjects used in this study was obtained in accordance with Air Force Regulation 169-3.

References

[1] Allum JHJ, Tole JR, Weiss AD. MITNYS-II - A digital program for on-line analysis of nystagmus. IEEE Trans. Biomed. Eng. 1975; BME-22(3):196-202.

[2] Anzaldi E, Mira E. An interactive program for the analysis of ENG tracings. Acta. Otolaryngol. 1975; 80:120-7.

[3] Arzi M, Magnin M. A fuzzy set theoretical approach to automatic analysis of nystagmic eye movements. IEEE Trans. Biomed. Eng. 1989; BME-36(9):954-63.

[4] Baland JF, Godaux ER, Cheron GA. Algorithms for the analysis of the nystagmic eye movements induced by sinusoidal head rotations. 1987; IEEE Trans. Biomed. Eng. BME-34(10):811-6.

[5] Baloh RW, Langhofer L, Honrubia V, Yee RD. On-line analysis of eye movements using a digital computer. Aviat. Space Environ. Med. 1980; 51(6):563,67.

[6] Barnes, GR. A procedure for the analysis of nystagmus and other eye movements. Aviat. Space Environ. Med. 1982; 53(7):676-82.

[7] Bednar JB, Watt TL. Alpha-trimmed means and their relationship to median filters. IEEE Trans. Acoust. Speech, Signal Processing, 1984; AASP-32(1):145-53.

[8] Bohmer A, Pfaltz CR. Interaction of vestibular and optokinetic nystagmus in patients with peripheral vestibular and central disorders. Oto-Rhino-Laryngol. 1980; 42:124-41.

[9] Bovik AC, Huang TS, Munson DC. A generalization of median filtering using linear combinations of order statistics. IEEE Trans. Acoust. Speech, Signal Processing, 1983; AASP-31(6):1342-50.

[10] Buizza A, Schmid R, Zanibelli A, Mira E, Semplici P. Quantification of vestibular nystagmus by an interactive computer program. Oto-Rhino-Laryngol., 1978; 40:147-59.

[11] Engelken EJ, Stevens KW, Wolfe JW. Application of digital filters in the processing of eye movement data. Behav. Res. Meth. Inst. 1982; 14(3):314-9.

[12] Furman JM, O'Leary DP, Wolfe JW. Application of linear system analysis to the horizontal vestibulo-ocular reflex of the alert rhesus monkey using pseudorandom binary sequence and single frequency sinusoidal stimulation. Biol. Cybernetics, 1979; 33:159-65.

[13] Gallagher NC, Wise GL. A theoretical analysis of the properties of median filters. IEEE Trans. Acoust. Speech, Signal Processing, 1981; ASSP-29(6):1136-41.

[14] Heinonen P, Neuvo Y. FIR-median hybrid filters. IEEE Trans. Acoust. Speech, Signal Processing, 1987; ASSP-35(6):832-8.

[15] Heinonen P, Neuvo Y. FIR-median hybrid filters with predictive FIR substructures. IEEE Trans. Acoust. Speech, Signal Processing, 1988; AASP-36(6):892-9.

[16] Hogg RV. Adaptive robust procedures: A partial review and some suggestions for future applications and theory. J. Am. Stat. Assoc. 1974; 69(348):909-23.

[17] Honrubia V, Baloh RW, Yee RD, Jenkins HA. Identification of the location of vestibular lesions on the basis of vestibulo-ocular reflex measurements. Am. J. Otolaryngol. 1980; 1(4):291-301.

[18] Lee YH, Kassam SA. Generalized median filtering and related nonlinear filtering techniques. IEEE Trans. Acoust. Speech, Signal Processing, 1985; ASSP-33(3):672-83.

[19] Longbotham HG, Bovik AC. Theory of order statistic filters and their relationship to linear FIR filters. IEEE Trans. Acoust. Speech, Signal Processing, 1989; ASSP-37(2):275-87.

[20] Nodes TA, Gallagher NC. Median filters: Some modifications and their properties. IEEE Trans. Acoust. Speech, Signal Processing, 1982; ASSP-30(5):739-46.

[21] Peterson SR, Lee YH, Kassam SA. Some statistical properties of alpha-trimmed mean and standard type M filters. IEEE Trans. Acoust. Speech, Signal Processing, 1988; ASSP-36(5):707-13.

[22] Restrepo A, Bovik AC. Adaptive trimmed mean filters for image restoration. IEEE Trans. Acoust. Speech, Signal Processing, 1988; ASSP-36(8):1326-37.

[23] Wall C III, Black FO. Algorithms for the clinical analysis of nystagmus eye movements. IEEE Trans. Biomed. Eng. 1981; BME-28(9):638-46.

[24] Wolfe JW, Engelken EJ, Olson JE. Low-frequency harmonic acceleration in the evaluation of surgical treatment of Meniere's disease. Adv. Oto-Rhino-Laryngol. 1979; 25:192-6.

[25] Wolfe JW, Engelken EJ, Olson JE. Low-frequency harmonic acceleration in the evaluation of patients with peripheral labyrinthine disorders. In: Honrubia V, Brazier MAB, ed. Nystagmus and vertigo: Clinical approaches to the patient with dizziness. New York:Academic Press, Inc., 1982:95-105.

[26] Wolfe JW, Engelken EJ, Stevens KW, Olson JE. Single sinusoids compared with a multiple-sinusoids technique for evaluating horizontal semicircular canal function. Aviat. Space Environ. Med. 1986; 57:667-70.

FIGURE CAPTIONS

FIGURE 1. Block diagram of the analysis program. The program consists of a series of three digital filters.

FIGURE 2. Smoothing filter results. A particularly noisy 10-s segment of nystagmus is processed by the PFMH filter. Top trace is the noisy input signal, the five following traces are successively filtered versions of the signal. After the fifth pass, the nystagmus signal is very near to a root signal.

FIGURE 3. One-second windows of nystagmus velocity samples are displayed in each of the four panels. Top trace in each panel shows the time-ordered samples; bottom trace, the rank-ordered samples. The bar graphs to the left of the traces are the frequency histograms of the samples. Note that rank-ordering the samples does not alter the histograms. Panel **A** shows a window with frequent high-velocity fast-phases. In **B** frequent low-velocity (70 deg/s) fast-phases are encountered; in **C** and **D** malformed fast-phases and/or eye-blink artifacts are encountered. In each case, the dominant mode of the histogram indicates the location of the SPV data samples. The arrows on the rank-ordered traces indicate the samples selected for averaging by the AATM filter.

FIGURE 4. Block diagram of the AATM filter. Velocity samples from a moving window are rank-ordered and the skewness of the frequency distribution is calculated. Then the skewness measure is used to adaptively select a subset of the samples for averaging. The averaged samples constitute the estimated SPV.

FIGURE 5. Overall program performance on noisy nystagmus records. Each panel shows the estimated SPV superimposed upon the eye-velocity signal. A human volunteer was subjected to sinusoidal whole-body rotation about the vertical axis at 0.05 Hz, 60 deg/s peak velocity. Rotations were done in both light and darkness. The panels on the left show "light" responses; panels on the right, "dark" responses. Top panels show a complete cycle of rotation (20 s); bottom panels, an expanded view of the first quarter-cycle. For this illustration, the nystagmus signal was filtered once by the PFMH smoothing filter.

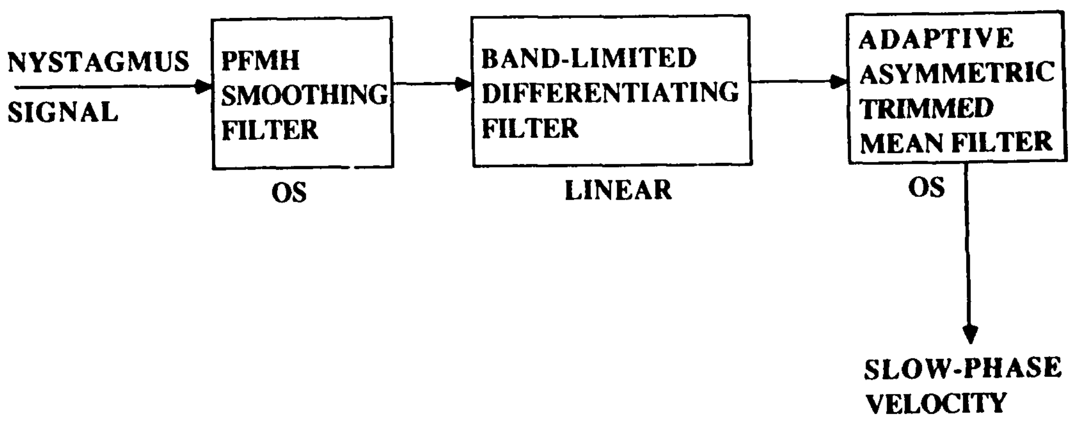

NYSTAGMUS
SIGNAL
PFMH SMOOTHING FILTER
OS
BAND-LIMITED DIFFERENTIATING FILTER
LINEAR
ADAPTIVE ASYMMETRIC TRIMMED MEAN FILTER
OS
SLOW-PHASE VELOCITY

FIG. 1

FIG 2

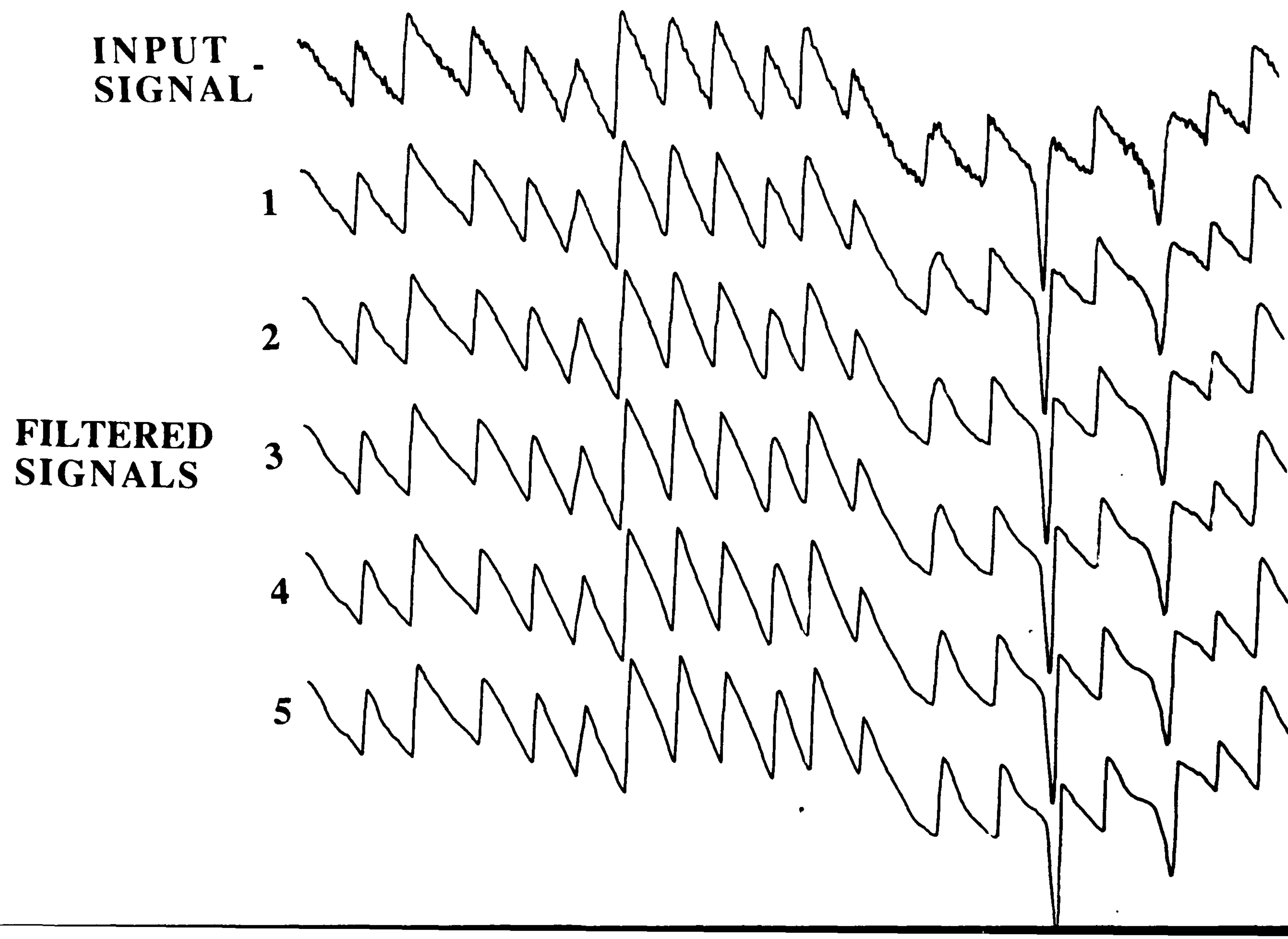
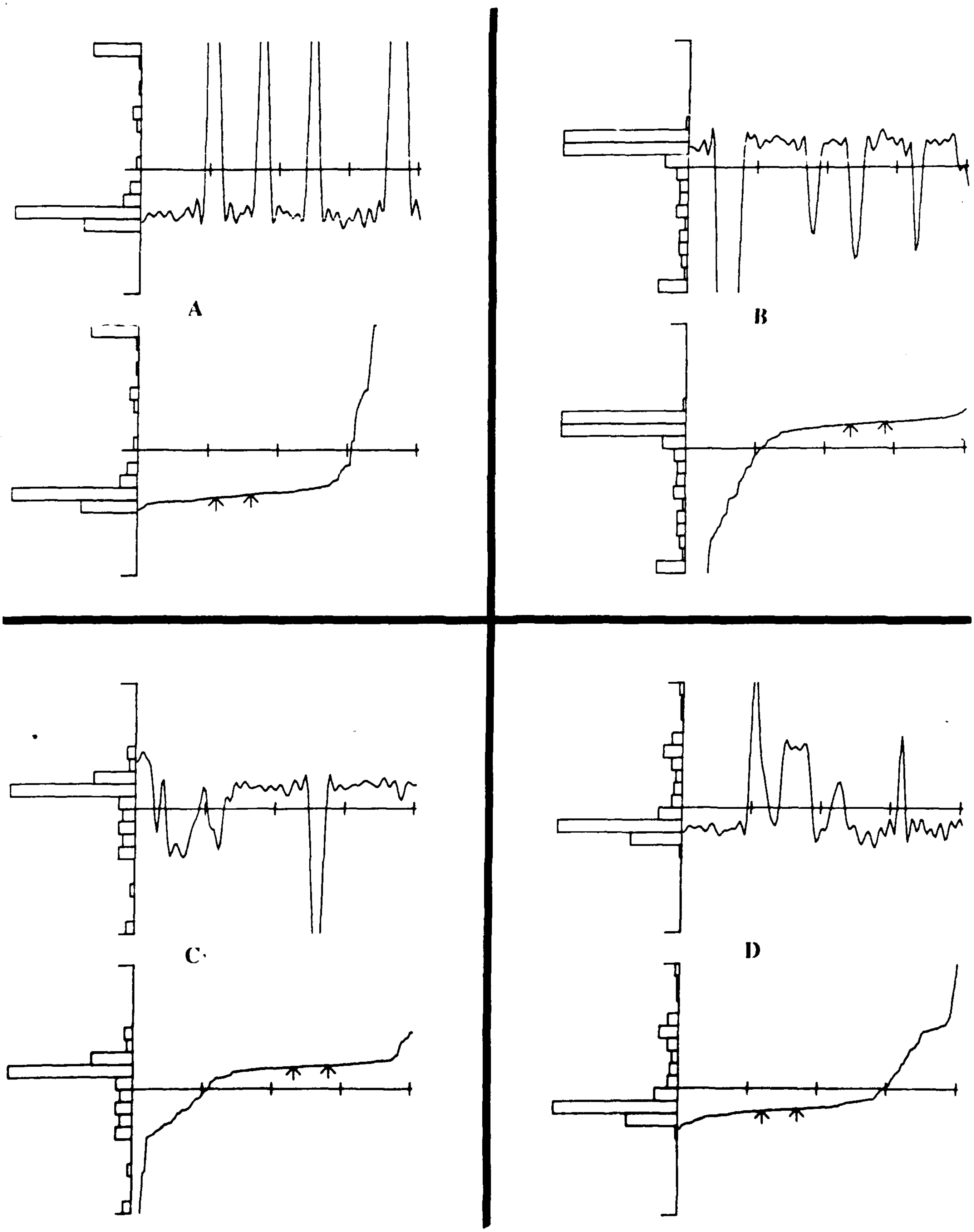


FIG-3



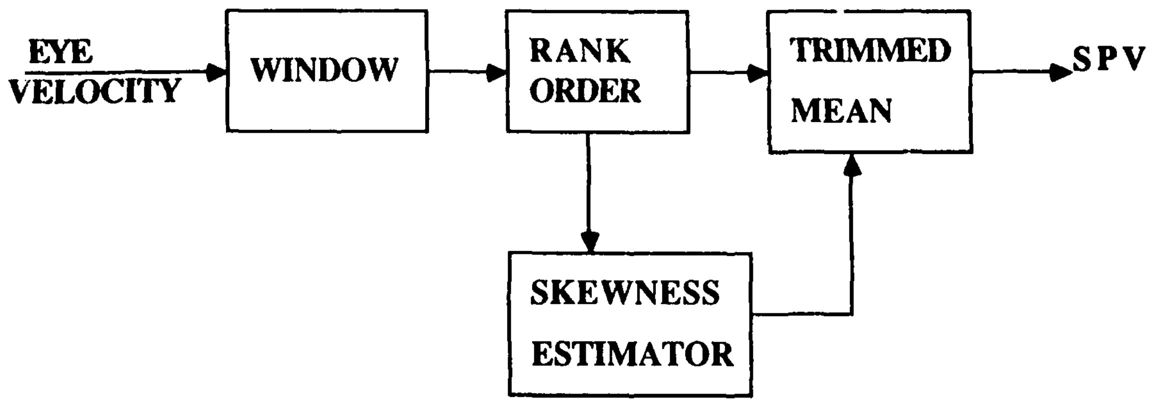

EYE
VELOCITY
WINDOW
RANK
ORDER
TRIMMED
MEAN
SPV
SKEWNESS
ESTIMATOR

Fig. 4

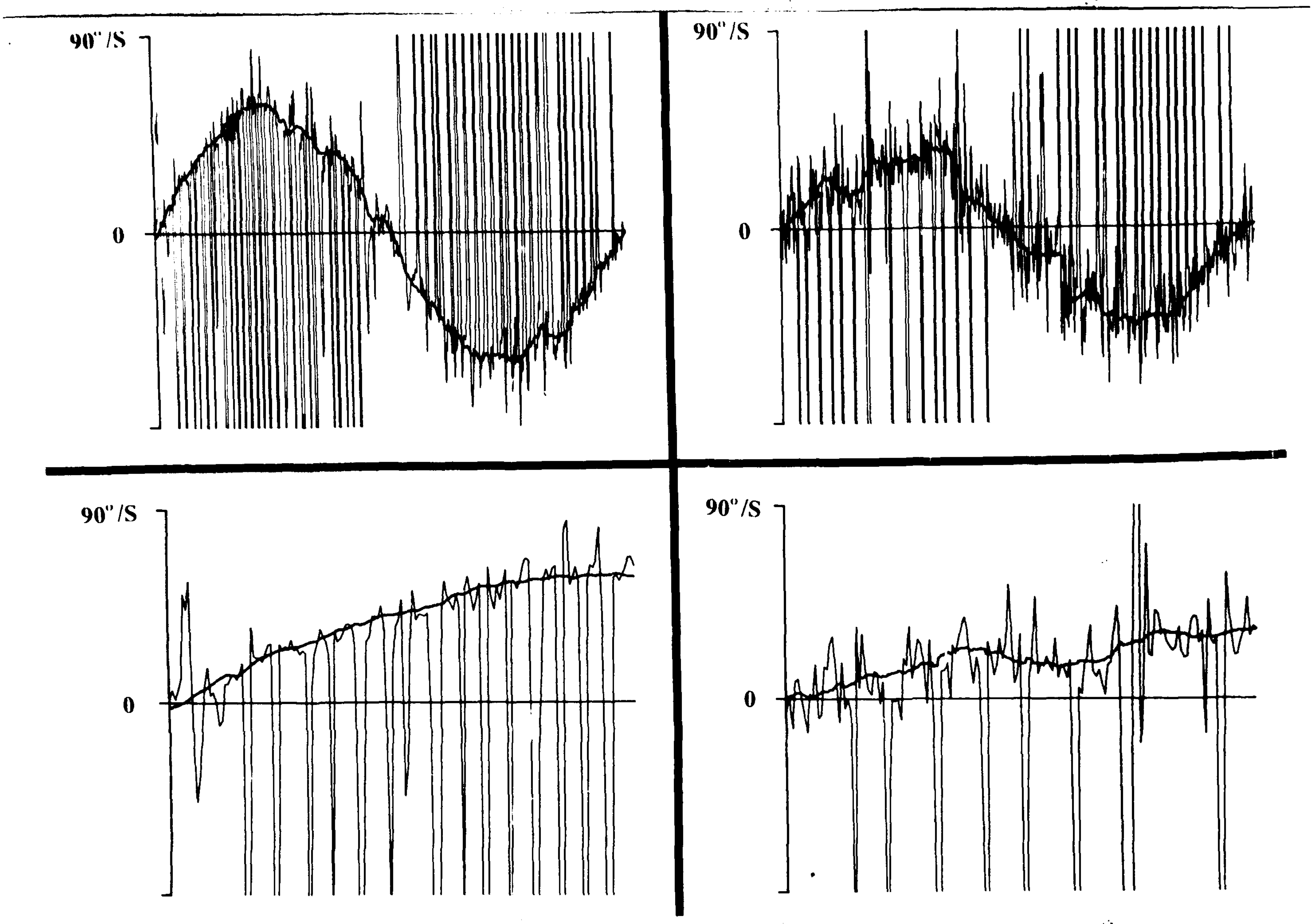


FIG. 5